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Forecasting Energy Consumption of Institutional Buildings in Singapore

Chirag Deb[a,*], Lee Siew Eang[a], Junjing Yang[a], Mattheos Santamouris[a,b]

[a]*Department of Building, School of Design and Environment, National University of Singapore 117566, Singapore*
[b]*Physics Department, Group Building Environmental Research, National and Kapodistrian University of Athens, Athens 15784, Greece*

Abstract

This study presents building energy forecasting methodology for cooling load for three institutional buildings. These buildings belong to a university campus in Singapore. The daily energy consumption for cooling load is obtained for a period of two years and the daily variation is analysed. The energy consumption is initially divided into five classes and the class numbers are used as inputs to develop a forecasting model. The model is developed using two machine learning tools. The tools used are Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Interface System (ANFIS). The division of data for training and testing the model is nearly 60% and 40% respectively. The results show that both ANN and ANFIS forecast the cooling load energy consumption of the three buildings with good accuracy. The correlation coefficient between measured and predicted consumption for training data are well above 0.98. The same is well above 0.96 for testing data. It is noted that such a methodology can be positively extended to other institutional buildings in the campus.

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Keywords: Energy forecasting; Machine learning tools; Prediction models; Institutional buildings.

1. Introduction

Building energy forecasting has gained momentum with increase in building energy efficiency research. Energy forecasting can be put into a number of useful applications. It can provide an initial check for facility managers and

* Corresponding author.
E-mail address: chirag.arian@gmail.com

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building automation systems to mark any discrepancy between expected and actual energy use. It can also be used as a cleaning technique for collected energy data which is often noisy. A large variety of forecasting methods have been identified for short term energy consumption. Most of them are based on ANN and their developments [1-3].

The complexity of building energy systems makes ANN a suitable tool in performing non-linear analysis. ANNs are a network of individual units known as 'neurons' arranged in layers. In a typical network, each neuron of a particular layer is connected to all the neurons in the next layer. The connections between neurons are known as 'weights'. The objective of developing a neural network is to assign suitable numerical values to these weights. This is done through the training process where the network is fed a set of input and output data. The network learns through these input-output combinations adjust the weights accordingly. The ANNs can learn from historical pattern during the training process. In this study, a typical feedforward neural network is used. A feedforward network is the one in which the information moves in only one direction, forward, from the input neurons, through the hidden neurons (if any) and to the output neurons. There are no cycles or loops in the network.

Recently, a number of researchers have emphasized neuro fuzzy systems (ANFIS) which combine the fuzzy if-then rules into a neural network-like structure. This was initially proposed by Jang in 1993 [4]. The architecture of the ANFIS used in this study is the first order Takagi-Sugeno model [5] which is quite popular in building energy forecasting studies. An example of this is the study done by Li et al. [6]. Such a model consists of five layers where each layer contains several nodes described by a node function. The node functions in the first and fourth layer are adaptive, or changeable while others in layer second, third and the fifth layers are fixed. The parameters of the adaptive nodes can be altered to optimize the performance by one or more learning algorithms. For this study, the learning algorithm used is the standard backpropagation algorithm.

2. Methods

To fully understand and manage energy use and performance of buildings, good quality measured data from energy monitoring systems and building energy management and control systems are crucial. Unfortunately for most buildings, only one electric meter is usually installed. This study utilizes the cooling load data collected at every thirty minutes interval. This data is then added to compute the daily energy consumption. All the three buildings (referred to as building A, B and C respectively) are part of the same school but vary in function. Building A mostly consists of offices, building B consists of offices and laboratories whereas building C consists of classrooms and seminar halls. The daily cooling energy consumption for the three buildings is presented in Fig. 1, 2 and 3 respectively.

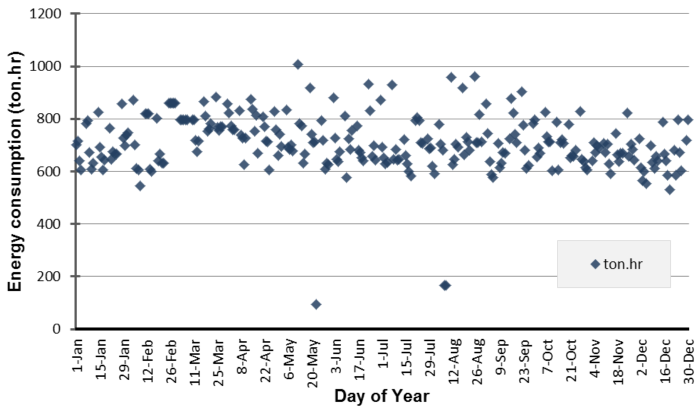

Fig. 1. Daily energy consumption variation for building A.

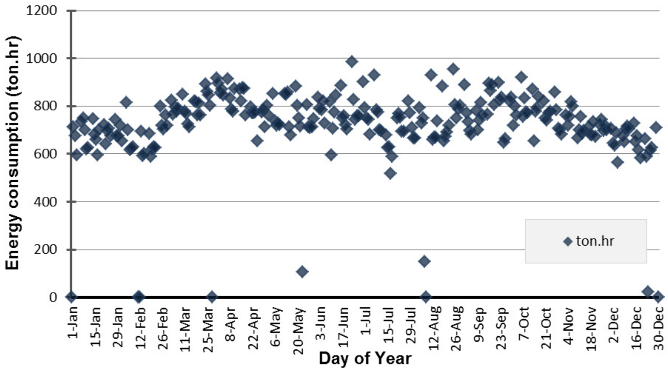

Fig. 2. Daily energy consumption variation for building B.

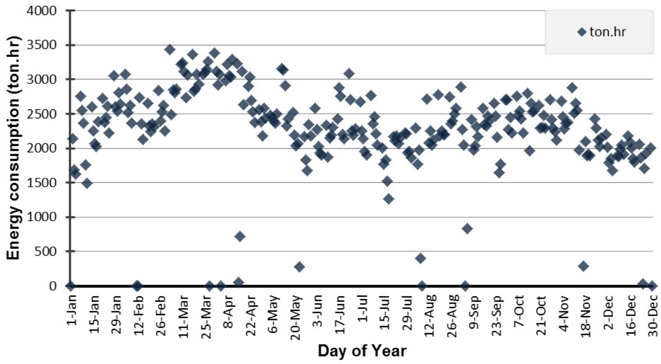

Fig. 3. Daily energy consumption variation for building C.

The figures show that there is good variation in the daily energy consumption. For some days, the energy consumption is nearly equal to zero. These are the holidays in which the central chiller plant serving the three buildings is switched off. These days are excluded from the data set. In many studies, the climatic variables are used as inputs for the forecasting model. The most common climatic variables are the air temperature, humidity and solar radiation. However in this study, a preliminary correlation show that the cooling load energy consumption does not relate well with the climatic variables. This clearly indicates that the air conditioning systems run independently of the outdoor conditions. This holds true for all the three buildings. Table 1 shows the correlation R^2 values for the three buildings with respect to the three climatic variables. With respect to humidity and solar radiation, there is no clear trend and the plot is significantly scattered, generating very low correlation coefficient values. It may be therefore concluded that the outdoor climatic condition has no effect on the energy consumption and these variables may be of no effect in model development.

Table 1. R2 values for cooling load consumption with respect to the three climatic variables.

Building	Air. Temp.	Humidity	Solar radiation
A	0.204	0.003	0.002
B	0.242	0.002	0.121
C	0.09	0.001	0.003

As observed, the climatic variables have a poor influence on energy consumption. Moreover, the occupancy data is not readily available as the cluster of these three buildings has many openings for occupants to enter and exit. All such factors make it difficult to measure an exact occupancy count. For these reasons, the focus is given to investigate on the internal energy consumption pattern. This means that rather than developing a model based on external factors as inputs (like climatic variables, occupancy etc.), the internal consumption pattern is assessed and the daily energy consumption for cooling is taken as inputs to predict the forthcoming days. The scale of data analyzed is on the yearly level. For this, average daily consumption is taken as an assessment element and the daily energy consumption is taken as inputs. Moreover, the weekend energy data is excluded from this analysis as the building is officially closed during these times. Excluding the weekends, there are about 250 data points (one for each day) and each value corresponds to the average energy consumption value for that day. The first level of analysis entails predicting energy consumption data for next successive day using the past data for previous three days. A graphic example of this is presented in Fig. 4.

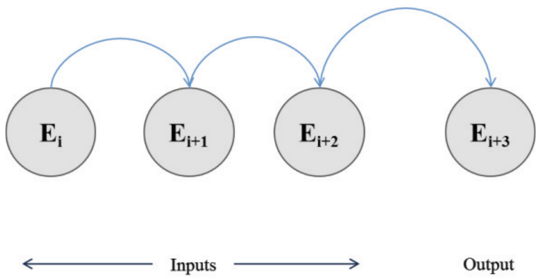

Fig. 4. Previous three days energy data used to predict consumption on the fourth day.

2.1. Data classes

In all, the data is divided into five classes and later distributed as twenty-five class numbers. Table 2 shows the division of classes. For example, class number '1' implies Mondays with low energy consumption, whereas, class number '18' implies Thursdays with average energy consumption. The class division would enable better understanding of the energy use sequence. These class numbers form the input variables for the next day energy consumption predictions based on three previous days' energy consumption data.

Table 2. Division of data into 25 class numbers

Energy class		1	2	3	4	5
Class numbers	Monday	1	2	3	4	5
	Tuesday	6	7	8	9	10
	Wednesday	11	12	13	14	15
	Thursday	16	17	18	19	20
	Friday	21	22	23	24	25

2.2. Artificial neural network

The Artificial neural network (ANN) modelling is done in MATLAB and the network selected here is the feed forward neural network. The training algorithm used is the Bayesian regularization algorithm and the division of data for training and testing the model is of the order of 65% and 35% respectively. The ANN architecture used here is the 3-3 structure (Fig. 5). This means that there are three input neurons and three hidden neurons. The three input neurons correspond to the three inputs. The single output neuron corresponds to the predicted fourth day energy consumption.

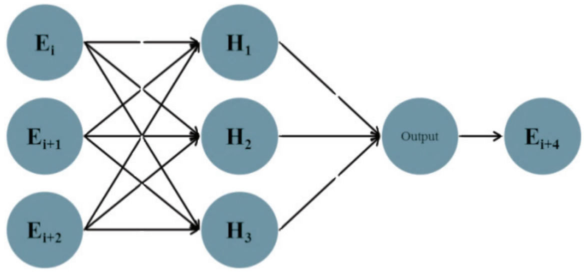

Fig. 5. The 3 layer ANN structure used in this study.

2.3. Adaptive neuro fuzzy interface system

The Adaptive neuro fuzzy interface system (ANFIS) implemented in this study is a Sugeno-type model. Such an ANFIS model is a hybrid framework that is obtained by combining the concepts of fuzzy logic and neural networks. The model has a fuzzy inference system in the form of an adaptive network and a predictive tool that maps a given input data set to its corresponding output data set. In this study, Genfis 2 (of MATLAB) is taken as the fuzzy interface system. It is used to derive five fuzzy 'if-then' rules that govern the processing a set of input variables to produce a single predicted output. The output is then compared to the measured values to test the accuracy of the model. Each input variable is linked to five parameterized Gaussian-shaped membership functions (MFs) that represent its fuzzy linguistic labels (i.e. very low, low, medium, high and very high). The details of the MF parameters and the learning algorithms involved are not discussed here as the emphasis is given to the specific case of building energy forecasting. More details on the Sugeno-type ANFIS model can be found in study by Alasha'ary et al. and Zahedi et. al. [7,8].

3. Results

The result of the ANN using the above mentioned class values show good prediction accuracy. With previous three days' measured data as inputs, the model shows an accuracy of more than 0.97 for testing data set for all three buildings. It is to be noted that the division of data for training and testing purpose is of the ratio of 3:2. Such high prediction rate is attributed to the improved clarity of the data set that is fed to the neural network for training. Rather than providing crisp energy consumption values, the class numbers represent a better way of classifying energy data and make it easier to comprehend the existing pattern of energy use from one day to another. Fig. 6 shows the plot with measured and predicted values for building A using ANN. It is observed that the slope of the line is also close to one. Similar results for building B and C are presented in Table 3.

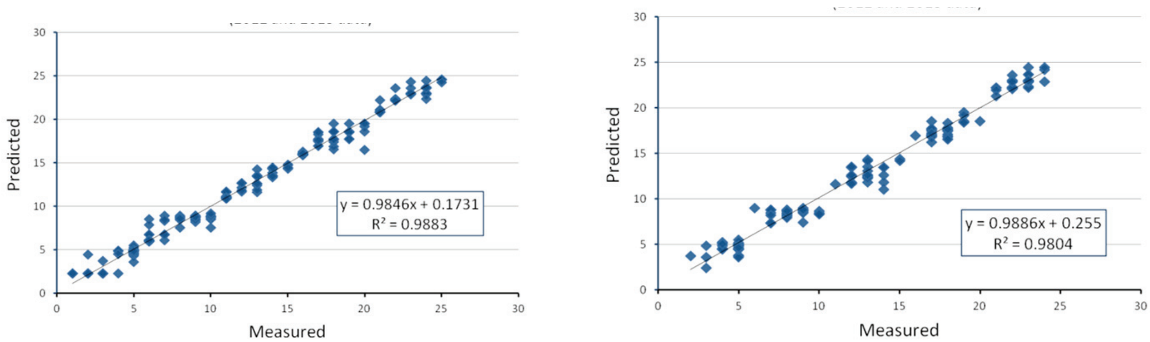

Fig. 6. Training and Testing results using Neural Net for building A.

It is observed that the prediction accuracy is slightly less for building C. This is attributed to the high variability in its operation as well as lack of clean data obtained from the meter. A table showing the number of sample data points collected is presented later. It is to be noted that the methodology used for prediction is similar for all the three buildings. The study initially was done with building B and was later extended to buildings A and C as well without changing the methodology. Therefore, it is encouraging to obtain these results even though the spread of the plot is not as streamlined for building C as is for A and B. however, the overall prediction accuracy is still very good.

A similar analysis is performed using ANFIS in MATLAB. The input set and output data used for training remains same as in the ANN model. Subtractive clustering is used for estimating the number and centers of rules. A sensitivity analysis is performed to determine the optimum radius for the clusters. It is found that a radius of 0.35 exhibits the best forecasting results for this set of input and output. Across the three buildings, the change in the radius is only of the order of 0.5 to 0.1 and can be conveniently scripted. The results obtained are presented in Table 3 and the plot for building A is presented in Fig. 7.

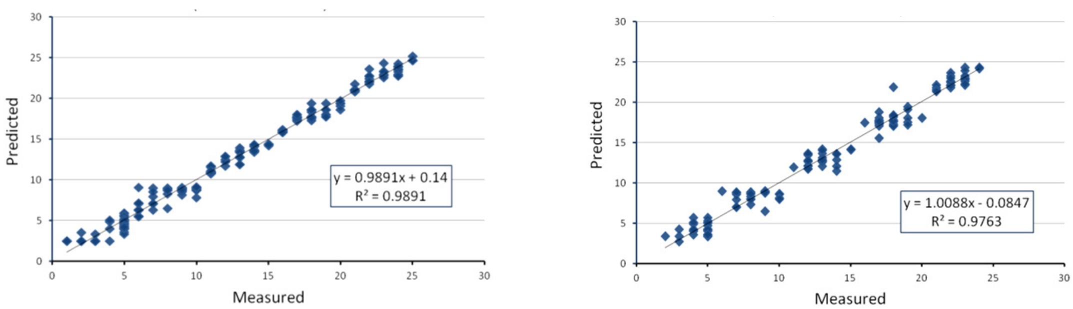

Fig. 7. Training and Testing results using ANFIS for building A.

A consolidated result showing the number of sample days used for training and testing as well as the prediction accuracy results for ANN and ANFIS is presented in Table 3.

Table 3. Consolidated results

Building A		Training	Testing
Number of sample days		250	147
Results (R^2)	Anfis	0.9891	0.9763
	Neural Net	0.9883	0.9804
Building B			
Number of sample days		250	122
Results (R^2)	Anfis	0.9845	0.9719
	Neural Net	0.9853	0.9712
Building C			
Number of sample days		120	77
Results (R^2)	Anfis	0.9867	0.9696
	Neural Net	0.9867	0.9700

4. Conclusions

This study presents a methodology and results for forecasting cooling load energy consumption for three institutional buildings in Singapore. The forecasting model is developed using ANN as well as ANFIS. It is observed that both ANN and ANFIS can forecast the energy consumption with good accuracy. For each building, the ANFIS model has to be slightly modified with respect to the radius of subtractive clustering. This parameter is used to assign rules in the ANFIS training process. Its value was taken as 0.3, 0.3 and 0.35 for buildings A, B and C respectively. For the ANN model, there was no major difference in the model development methodology across the three buildings. This shows that the same method can be positively extended to other institutional buildings as well. That forms the next phase of this project. The major inferences from this study can therefore be listed as follows.

The cooling load energy consumption in these buildings does not exhibit any significant correlation with the outdoor climatic variables. Hence, it is concluded that the outdoor climate does not influence the cooling load energy use of these buildings.
The ANFIS model is also very effective in forecasting energy consumption based on previous data. There is a slight variation in the model parameters across the three buildings but it can be conveniently scripted.

- The cooling load energy consumption in these buildings does not exhibit any significant correlation with the outdoor climatic variables. Hence, it is concluded that the outdoor climate does not influence the cooling load energy use of these buildings.

- The feed forward ANN used in this study is able to forecast the energy consumption of next day based on three previous days' energy data with good accuracy. The same neural network is applicable to all the three buildings. It is inferred that such a methodology can be positively extended to other institutional buildings in the campus as well.

- The ANFIS model is also very effective in forecasting energy consumption based on previous data. There is a slight variation in the model parameters across the three buildings but it can be conveniently scripted.

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